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PARCIV: Recognizing Physical Activities having Complex Inter-class Variations using Semantic Data of Smartphone

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Smartphones are equipped with precise hardware sensors including accelerometer, gyroscope, and magnetometer. These devices provide real-time semantic data that can be used to recognize daily life physical activities for personalized smart health assessment. Existing studies focus on the recognition of simple physical activities but they lacked in providing accurate recognition of physical activities having complex inter-class variations. Therefore, this research focuses on the accurate recognition of physical activities having complex inter-class variations. We propose a two-layered approach called *PARCIV* that first clusters similar activities based on semantic data and then recognize them using a machine learning classifier. Our two-layered approach first bound the highly indistinguishable activities in clusters to avoid misclassification with other distinguishable activities and thereafter recognize them on a fine-grained level within each cluster. To evaluate our approach, we make an android application that collects labeled data by using smartphone sensors from ten participants, while performing activities. *PARCIV* recognizes distinguishable as well as indis-

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tinguishable activities with high accuracy of 99% on the self-collected dataset. Furthermore, *PARCIV* achieve 95% accuracy on the publicly available dataset used by state-of-the-art studies. *PARCIV* outperforms various state-of-the-art studies by 8-17% for simple activities as well as complex activities.

KEYWORDS
Semantic Data, Healthcare, Smartphone Sensors, Accelerometer, Complex Confused Activities, Inter-class Variations

1 | INTRODUCTION

Healthcare is enriched with semantic data representing information about the personal health of an individual. Semantic data depicts the relationships among data (i.e data obtained from smartphone sensors for activities such as fall detection and activity recognition). Despite such richness in the healthcare domain, not all the Machine Learning (ML) techniques in automated healthcare systems can work efficiently on semantic data. Right now, among the best generally utilized ML techniques for experimentation of semantic data are Support Vector Machine (SVM), Artificial Neural Network (ANN), and Random Forest (RF). Semantic data collected by smartphone sensors (accelerometer, gyroscope, and magnetometer) of daily life activities shares some common semantic information and characteristics about physical health assessment [1].

In automated healthcare systems, physical activity recognition is a challenging problem due to its practical applications like healthcare support, smart sports, elder-care and assisted living [2]. Physical activity recognition and assessment have a direct connection with an individual's health and physical fitness. Physical activity recognition improves the individual's health by monitoring and analyzing activities of daily life. In healthcare, doctors can examine the health conditions of individuals according to their performed activities [1]. In today's busy schedule, people want a healthy lifestyle. They pay more attention to their health, physical fitness, the suggestion and recommendations provided by the care providers [1, 2, 3, 4]. Physical inactivity is rising as a big issue nowadays. Several individuals face serious diseases due to a lack of physical activities. Authors in [5] stated that it is the 4^{th} leading risk factor for people. Also, blood pressure and obesity are quietly closed to physical inactivity [6]. Authors showed that physical fitness can decrease mental disorder, cancer, diabetes, muscle issues, weight issues, emotional issues, and depression as well.

Physical activity recognition was first initiated using on-body sensors. On-body Sensors were used back in 2004 by the study [7]. They placed bi-axial sensors at different body positions to detect 20 physical activities. The challenge in this scenario is to wear on-body sensors and carry them all the time. In state-of-the-art, smartphones have been extensively used for physical activity recognition [8, 1]. Smartphones embedded with various precise sensors (i.e., accelerometer, gyroscope and magnetometer) has replaced wearable devices due to its unobtrusive nature. It is easy to carry and today everyone has a smartphone. The availability of the smartphone is the biggest breakthrough in a computing environment. Smartphones are the most ubiquitous, non-obtrusive, reliable and beneficial source to recognize physical activities and other health-related issues (i.e., calories burned, heart rate monitoring) [9].

Many researchers reported that the accelerometer sensor is the most reliable and cheapest alternate of wearable sensors for physical activity recognition. Authors in [7, 8, 10, 11] analyzed that accelerometer can be used in combination with other sensors like gyroscope, light, proximity, barometer, linear acceleration and magnetometer for better activity recognition. Furthermore, there is a large increase in the inventions of daily monitoring systems that can detect the individual's health, lifestyle, activities, behavior, and emotions.

Existing work on physical activity recognition mainly focused on six basic activities: *walking*, *standing*, *sitting*, *running*, *upstairs and downstairs* which are quite normal daily life activities and can be recognized easily. While other complex activities have less discriminating information as they are very similar in behavior and pattern (e.g., upstairs with downstairs, cycling with upstairs, fast running with jogging, laying positions and sitting positions). Therefore these activities get confused with each other in the recognition process and hence results in misclassification.

To address the above limitations, we make the following contributions.

- Propose a two-layered approach named *PARCIV* for physical activity recognition having Complex Inter-class variations.
- *PARCIV* first clusters the activities having complex inter-class variations based on semantic data and then recognize them on a fine-grained level within each cluster.
- Provide pattern analysis of 15 types of complex physical activities.
- Evaluate *PARCIV* on a self collect dataset from 10 participants and publically available datasets.
- *PARCIV* achieved promising results on the self-collected dataset as well as on publically available datasets used in state-of-the-art studies.

The remainder of the paper is structured as follows: Section 2 presents the related work on physical activity recognition, Section 3 describes the proposed approach for physical activity recognition and Section 4 shows the experimental setup containing evaluation measures, activity representation analysis, dataset, comparisons of results and discussion. Section 5 concludes the paper and shows the future direction.

2 | LITERATURE REVIEW

In this section, we present the related studies focusing on physical activities using streaming data collected either by smartphone or on-body sensors as well as other studies related to healthcare. In healthcare applications, the use of semantic data may extraordinarily improve the worthiness of data by using machine learning methods [12, 13, 14, 15]. Healthcare data collected by smartphone sensors of activities of daily life share some common semantic information and characteristics. A smartphone is equipped with precise sensors like Motion sensors, Environmental sensors, Position sensors. Motion sensors such as accelerometer, gyroscope, and magnetometer are the most valuable and well-studied sensors for physical activity recognition. The study [7] presents an approach which identified physical activities with the bi-axial accelerometer on 5 body positions: hip, wrist, upper arm, ankle, and thigh. They used Decision Tree (DT) C4.5 and Naive Bayes (NB) ML techniques for classification. After applying the ML techniques, they show that the data collected from the thigh position shows higher accuracy than the data of all other positions. Some other studies [7, 8, 11] used a similar approach for physical activity recognition. The study [16] collected data from 29 individuals of an educational institute using an android application at the sampling rate of 20 samples per second (20/sec). The smartphone was placed in the participant's pocket. They selected a static window of 200 samples to apply the predictive models. They applied three classification methods: DT (j48), Logistic Regression (LR) and Multilayer Perceptron (MLP) using ten-fold-cross-validation.

Some studies also preferred dynamic window size over static window size for classification process [17, 18, 19]. They collected data at different frequencies. The study [17] shows that the data collected at different frequencies can positively affect the overall performance of activity recognition as well as the energy consumption of the battery. They collected data at different frequencies (i.e. 5hz, 16hz, 50hz, and 100hz) and saved battery energy by 50%. A similar study [18] proposed a low energy physical activity recognition system using a smartphone. They used the discrete variables that were obtained from the accelerometer sensor. A discretization process was used for each variable that drains very little energy. The approach determined the performed activity and the frequency at which it is performed. Furthermore, the technique saved a lot of battery power up to 27 hours while maintaining accuracy. Data were collected from 10 users with different smartphones. Ameva algorithm was used to help the new algorithm in the discretization process.

The study [20] brings some changes in the behavior of getting data from the accelerometer and applying ML techniques on it. First, they divide the data collected from a tri-axial accelerometer into short non-overlapping windows and then convert each window into a feature vector. For supervised learning, they treated each instance as an independent identical distributed training instance. A multi-scale ensemble method applied for activity recognition as some activities have repetitive behavior. However, their experiments show low results for upstairs, lying, downstairs, walk and jogging activities. The study [10] provides a comprehensive survey on human activity with all available sensors in the smartphone. These sensors include accelerometer, ambient temperature, gyroscope, linear acceleration, magnetometer, barometer and proximity sensor. The study [8] introduced a framework to recognize physical activities. The framework collects accelerometer data from 10 participant's smartphones with a rate of 50 samples per second (50/sec). They used a fixed size window approach to segment the data. A total of 100 sample window was selected to apply the ML algorithm. They analyzed, when and how to use sensors individually or in combination. They choose five body positions right pocket, left the pocket, on the belt, right upper arm, and right wrist. They investigate the performance of the data collected from single and multiple participants.

The research work [11] analyzed that the motion recognition is a difficult step to recognize or even it can be worse if the motion is showing repetitions and abnormal behavior like walking and fast walking, sharp turn upstairs and downstairs. Authors combined the latest positioning technologies and sensors to capture human movements in natural environments. They investigated some common motion states like standing, sitting, walking, lying, fast walking, U-Turn, and sharp turn. They observed that the static states like sitting, lying, and standing are easy to recognize, but dynamic states like U-Turn and sharp turn are difficult to recognize. Similarly, the study [21] worked on activity recognition by placing the smartphone in different positions and orientations. They used smartphone sensors like accelerometer, gyroscope, proximity, light, and magnetometer sensor. Data were analyzed in a sense either the smartphone was in the participant's pants pocket or shirt's pocket or hand by using light and proximity sensors. They used decision tree j48, naive bayes and support vector machine for activity recognition.

By considering the effect of flexibility in orientation of smartphone, placement of smartphone and participant's variations, the study [22], proposed an approach based on the Coordinate Transformation and PCA. For decreased performance due to the inherent difference in signal properties of different types of placement, they used Online SVM. The study [23] highlights that the accurate recognition of activities depends on the efficient feature selection method from the time series data. They proposed an approach for dynamic feature extraction and then the results of dynamic and static features were compared. They analyzed that the Convolutional Neural Networks (CNN) provides a better recognition rate with dynamic features rather than other common ML algorithms (i.e., MLP, SVM, and k-nearest neighbor(KNN)).

Authors in [24] first extracted features (mean, median, auto-regressive coefficients, etc.) from the raw dataset. They applied Linear Discriminant Analysis (LDA) and Kernel Principal Component Analysis (KPCA) to make these features robust. They trained the Deep Belief Network (DBN) for recognition of activities. The comparison was shown with the traditional approaches: SVM and ANN. An unsupervised approach was proposed by [2] to classify physical activities using the smartphone accelerometer sensor. They gathered data on normal life exercises and made an undirected graph utilizing Euclidean Distance (ED). This diagram was then passed to the MCODE clustering algorithm to group daily life activities.

An approach [25], recognize daily routine activities by classifying semantic data on the remote server. They used one smartphone having an accelerometer to collect data at the frequency of 100 samples per second and used a static window technique to segment the data. The smartphone was placed in the subject's pocket to gathered all the activities data. Later, they applied 10 ML techniques on the data to recognize activities remotely. The study [26] presented a methodology for elderly people to assist them in their daily life activities. They used the Ameva algorithm to reduce battery consumption. They reported that the combination of the gyroscope, magnetometer, and barometer resulted in the improvement of the recognition rate.

To the best of our knowledge, existing physical activity recognition approaches either only consider simple activities (e.g. walking, running, standing, sitting and cycling) or have low recognition rate to recognize activities having complex inter-class variations (e.g. upstairs, downstairs, lying positions, cross-legs, jogging, and fast walking). Moreover, existing studies have not performed the pattern analysis information of complex activities. Table 1 presents an overview of which smartphone sensors, sampling frequency, sliding window and dataset used by state-of-the-art studies. Table 2 presents an overview of several individuals, smartphone sensors and sensors placing positions used by state-of-the-art studies.

TABLE 1 Sensors and Datasets used in Related Work

Type	-	[8]	[25]	[27]	[26]	[10]	[20]	[11]	[18]	[21]	[7, 28]	[16]	[29]	[30]	[17]	[19]
	Accelerometer	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Magnetometer	✓	-	-	-	✓	-	✓	-	✓	-	-	-	-	-	-
	Light Sensor	-	-	-	-	✓	-	-	-	✓	-	-	-	-	-	-
Sensors	Gyroscope	✓	-	-	-	✓	-	✓	-	✓	-	-	-	-	-	-
	Proximity	-	-	-	-	✓	-	-	-	✓	-	-	-	-	-	-
	Barometer	-	-	-	-	✓	-	-	-	-	-	-	-	-	-	-
	Linear Accel.	✓	-	-	-	✓	-	-	-	-	-	-	-	-	-	-
	10-50	-	✓	-	-	-	✓	✓	-	✓	✓	✓	✓	✓	✓	✓
	100	✓	-	-	-	-	-	-	-	-	-	-	-	-	✓	-
Sampling	125	-	-	-	✓	-	-	-	-	-	-	-	-	-	-	-
Frequency	128	-	-	✓	-	-	-	-	-	-	-	-	-	-	-	-
	200	-	-	-	-	-	-	-	✓	-	-	-	-	-	-	-
Sliding Window	-	-	-	-	-	-	-	-	✓	-	-	-	-	-	✓	✓
	Self	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dataset	Publicly	-	-	-	✓	-	-	-	-	-	-	-	-	-	-	-

TABLE 2 Setup for Data Collection in Related Work

Type	Setup	References
Individuals	Single	[19]
	Multiple	[8, 25, 27, 26, 20, 18, 7, 7, 16, 29, 28, 30]
Single Sensor	Single Accelerometer	[25, 27, 20, 18, 7, 16, 28, 30, 19]
	Multiple Accelerometer	[8, 10, 11, 7]
Multiple Sensors	Accelerometer, Magneto, Gyroscope, Linear Acceler	[8]
	Acceler, Magneto, Light Sen, Proxi, Barome, Gyro, Linear Acc	[10]
	Accelerometer, Magnetometer, Gyroscope	[11]
	Accelerometer, Magnetometer, Light Senor, Proximity, Gyroscope	[21]
Sensor Position	Pocket	[8, 25, 27, 26, 11, 7, 16]
	Arm, Knee, Waist, Pocket, Abdomen, Thigh	[20, 7, 28, 30]
	Hip	[18]

3 | PROPOSED METHODOLOGY

In this section, we explain our proposed approach named PARCIV: Physical Activity Recognition having Complex Inter-class Variations. Figure 1 summarizes our proposed approach. Below we describe algorithm description, data collection, sensing application, preprocessing, data balancing and classification models for activity recognition.

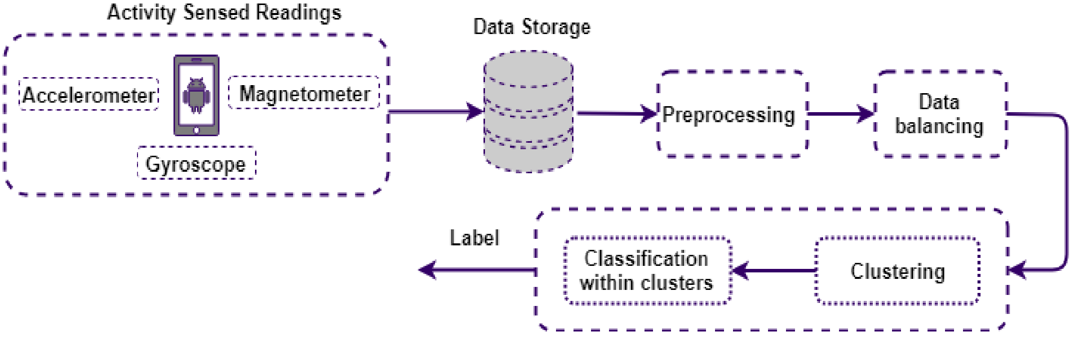


FIGURE 1 Block Diagram for the Proposed Approach

3.1 | PARCIV Algorithm Description

The feature matrix consisting of semantic data of activity instances I_{ji} of activity A_i is given to a ML model K-means to group the instances of similar activities into clusters S_{uk}. Each cluster S_{uk} come into existence by minimizing the error objective function that measures the distance of each activity instance from their respective cluster center given as

$$\sum_{u=1}^{U_k}\sum_{j=1}^{J}||I_{jk} - C_{uk}||^2 \tag{1}$$

where C_uk is cluster center for each cluster S_{uk}. Then each instance UK_i of each cluster S_{uk} is given to classifier kNN which returns a label L^{A_i} on the basis of nearest neighbour.
$I : total\ number\ of\ activity\ classes$;
$J : total\ number\ of\ activity\ instances\ per\ class$;
$A_i : i^{th}\ activity\ class$
$I_{ji} : j^{th}\ instance\ of\ activity\ i^{th}\ class$;
$S_{uk} : u^{th}\ clusters\ of\ activity\ A_i$;
$UK_i : i^{th}\ instance\ of\ u^{th}\ cluster$;
$L^{A_i} : label\ of\ recognized\ activity\ class$;

Algorithm PARCIV Algorithm

```
procedure PARCIV(I_ji)
    for I_ji ∈ A_i do
        S_uk ← K − means (I_ji)
    return S_uk
    for UK_i ∈ S_uk do
        L^{A_i} ← kNN (UK_i)
    return L^{A_i}
```

3.2 | Data Collection

This section presents our data collection rules and protocols. We collect data from smartphones: *Oppo F3* and *Oppo F1s*. To perform physical activities, we voluntarily recruited 10 participants (mean age = 25.0 with a range of 21 to 30 years). Out of 10 participants, 9 were male and 1 was female. We ask participants to perform selected activities using a smartphone. While they perform activities, a smartphone was placed in the left pocket to capture the progress of the activity to its completion. This application permits us to control which sensor data (e.g., accelerometer, gyroscope, magnetometer) to collect and how frequently to collect. In all cases, we collected the data at a fixed frequency of 40 samples per second, so we had 2400 samples per minute. This frequency is fine enough to capture all required actions as recent studies show that the sensor invoking frequency is good between 10-50 samples per second [31, 18] in order save battery.

The data collection was supervised by our team members to ensure the quality of the data. Dataset consists of sensor events generated while performing the activities. Each activity was performed continuously for approximately 4-5 minutes except the upstairs and downstairs because it was difficult to gather data with the limited stairs and physical fitness of the participant. Not all participants performed each activity. Some participants performed ten activities and some performed 7. All the sensor readings were recorded in the comma-separated file (CSV). To ensure recorded reading are well organized we assigned a timestamp to each reading. In this way, our data set consists of 9 features and 1 label. For the ground truth data, we assigned labels manually to all the sensed readings as we have the ground truth information about the task being performed. Table 3 shows the characteristics of dataset. Illustration of activities posture is shown in Figure 2.

TABLE 3 Characteristics of the Collected Dataset

Dataset	Human Activity Recognition
Number of Participants	10
Mean Age	26
Health Condition	Healthy
Total Features	10
Total Activities	15
Dataset Property	Imbalance
Activities of Daily Life	Sitting Straight. Sitting Left Leg Over Right Leg Sitting Right Leg Over Left Leg Sitting Cross leg Walking with normal Speed Walking Fast Jogging Running Cycling Standing Upstairs Downstairs Laying Straight Laying Over Left Side Laying Over Right Side

FIGURE 2 Graphical Representation of the Activities

3.3 | Smart Phone Sensing Data Application

In this work, we make an android application *PARCIV*, run-able for every type of Android smartphone. For android, our minimum operating system requirement is 4.0, which covers the majority of Android devices [32]. Android allows applications to read data from smartphone sensors, while iOS has a much stricter policy that only allows third-party apps to collect data from a very limited set of sensors.

- It consists of a graphical user interface with an edit-text to label the performed activity as ground truth.
- A service was made to run continuously in the background to collect data from all three sensors.
- Three smartphone sensors accelerometer, gyroscope, and magnetometer were used to perform the data collection task. Data were collected at a fixed frequency of 40 samples per second.
- A service was programmed to flush all the data into a Comma Separated File (CSV) file when the back key was pressed.

3.4 | Data Preprocessing

In our data collection task 3.2, as explained that the data was collected by ten participants while the smartphone was kept in participant's left pocket in most cases. Noisy samples are generated when a participant places the smartphone in the pocket and removes the smartphone from the pocket. It took almost 2-3 seconds, which means 120-200 samples at the start and the end. To get reasonable results, we remove this noisy data from each activity.

3.5 | Data Balancing

In the case of imbalanced class distribution, the machine learning model does not work well [33, 34]. As studied in [33], SMOTE is used to increase the instances of the minority class. It creates a new instance of the minority class based on specified nearest neighbors of the minority class which improves the representation of the minority classes which results in improving the recognition performance of the ML model. To make a new instance it calculates the distance between an original instance and the nearest neighbors. Then it multiplies the new distance with the range between 0-1 and then it is added into the original instance thus a new instance comes into existence. Below we explain the example of generating synthetic instances.

Suppose a sample (1,2) and let (3,4) be its nearest neighbor. (1,2) is the sample for which k-nearest neighbors are being identified. (3,4) is one of its k-nearest neighbors.
Let:

$$\begin{aligned} Ds1_1 &= 1, \quad Ds2_1 = 2 \\ Ds1_2 &= 3, \quad Ds2_2 = 4 \end{aligned} \tag{2}$$

The new samples will be generated as

$$(Ds1', Ds2') = (1,2) + rand(0-1) * (3-1, 4-2) \tag{3}$$

where rand(0-1) generates a random number between 0 and 1.

3.6 | Machine Learning Model

We applied two machine learning algorithms to cluster and classify the activities. Below are the algorithms:

- **K-Means:** K-means is an iterative process that works on finding the mean between the examples and adding them to the cluster that has the least squared error [35]. This error can be calculated using distance formulas like Euclidean distance and Manhattan distance. Particularly, Euclidean distance is used to calculate the new means on which the new centroids are updated. This process is repeated until when there are no new assignments in the clusters.
  Given a set of n-dimensional samples $(i_1, i_2, ..., i_n)$ has been clustered into k-clusters$C_1, C_2, C_3, ..., C_n$. Each sample must be clustered into exactly one cluster. Initially means are randomly generated in the search space. The mean of each cluster is defined is by following equation:

$$Mean_j = (\frac{1}{n_j}) \sum \sum_{i=1}^{n_j} x_{ij} \tag{4}$$

Where $x_i k$ is the $i^t h$ instance belonging to the $k^t h$ cluster in the search space. The centroid of each of the k clusters becomes the newly made mean. Error within a cluster C_k is calculated as explained in following equation:

$$e_k^2 = \sum_{i=1}^{n_k} (x_{ij} - Mean_j)^2 \tag{5}$$

Where e_k^2 is the sum of error within the cluster. To calculate the sum of all the clusters following equation is used:

$$E_k^2 = \sum_{k=1}^{k} e_k^2 \tag{6}$$

Where k is the k_{th} cluster in the search space and total error is sum of errors of the cluster in the search space.

- **K-Nearest Neighbor :** The k-nearest neighbor (kNN) algorithm is a nonparametric technique used for both regression and classification [36]. In case of classification, given a n-dimensional input vector $(i_1, i_2, ..., i_n)$ with label Y lie in space and and p be the total number of features $(f_1, f_2, ..f_n)$. K is the number of nearest neighbors to which approximations are made with the test vector. An unlabeled example is assigned a labeled voted by nearest neighbors using ED as expressed in following equation 7 :

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (I_i(x) - I_i(y))^2} \tag{7}$$

$$y(x) = arg \max_{y \epsilon Y} \sum_{i=1}^{k} \delta(y, y(y_i)) \tag{8}$$

Where y_i is the nearest neighbor. and $\delta(y, y(y_i)$= 1 if $y = y(y_i)$ otherwise $\delta(y, y(y_i)$ = 0. Labeled is assigned to the test instance on the basis of ED between them. There are many other metrics but ED is one of the most common metric.

3.7 | Learning and Parameter Tuning

Below we explain classification algorithms and their parameters.

- K-Means : K-means is an iterative algorithm that works on finding the mean between the examples and adding them to the cluster that has the least squared error. The most important parameter is *distance function*. In our case, we chose *euclidean distance* as it was performing well in our case as compared to Manhattan distance. All other parameters were kept as default.
- K-Nearest Neighbor (kNN) : An unlabeled example is assigned a labeled voted by nearest neighbors using Euclidean distance. Two most important parameters are *distance function* and *number of nearest neighbor*. We chose Euclidean distance as distance function and K = 3 nearest neighbors. We got the best overall performance of 99% using the above-described parameters.

The next section explains the Evaluation and Results.

4 | EVALUATION

In this section, we explain our experiments, different performance measures for evaluation, present and discuss our results for the activity recognition. We perform different experimental analysis at different stages of the dataset to make it understandable for future use. We perform 10-fold cross-validation for evaluating the performance of the machine learning model.

4.1 | Evaluation Measures

Evaluation measures are a vital part to assess the performance of the classifiers. Almost all evaluation measures depend on the nature of the data. Mostly accuracy is taken as a basic measure but it is in the case when data is balanced. However, when the data is imbalanced, it does not provide reliable information. One can easily understand the performance of accuracy measures in case of data imbalance by seeing the confusion matrix. Below, we illustrate terms that can be useful for evaluation measure analysis.

Several measures are:

$$recall = \frac{TP}{TP + FN} \tag{9}$$

$$precision = \frac{TP}{TP + FP} \tag{10}$$

$$accuracy = \frac{TP}{N} \tag{11}$$

$$f - score = 2 \times \frac{precision \times recall}{precision + recall} \tag{12}$$

For a fair comparison, we use the same evaluation measures as used in base papers.

TP represents the true positive rate that is correctly classified instances, FN represents a false negative rate that is wrongly recognized instances. N represents total instances of all activities. FP represents False Positive rate that is samples of other activities wrongly recognized as one activity samples. The recall is calculated by dividing TP by $TP + FN$. Precision is calculated by TP dividing by $TP + FP$. Accuracy is calculated by TP divided by N. f-score is computed as the harmonic mean of recall and precision.

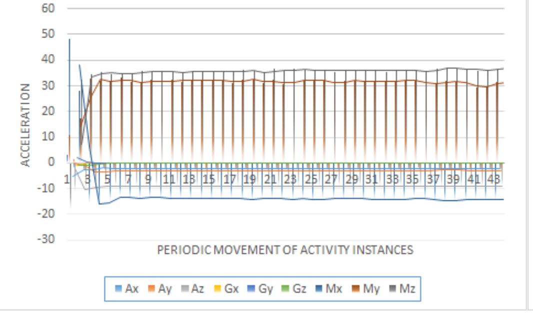
4.2 | Description of Experiments

For experiments, we collect labeled data from smartphone sensors and then preprocessed data to remove noise as explained in Section 3.4. Difficult activities like upstairs, downstairs, fast running, and fast walking requires more human energy than other activities, thus, instances of these activities are fewer than other activities. The collected data of each participant for each activity is cleaned and grouped based on having complex inter-class variations and sharing common semantic information using k-means clustering. We make 8 clusters for 15 activities as explained in the section activity representation 3 after analyzing the similarity between activities. Moreover, we analyzed different cluster numbers. After clustering, we use the k-Nearest Neighbor classifier to recognize activity instances from 8 clusters.

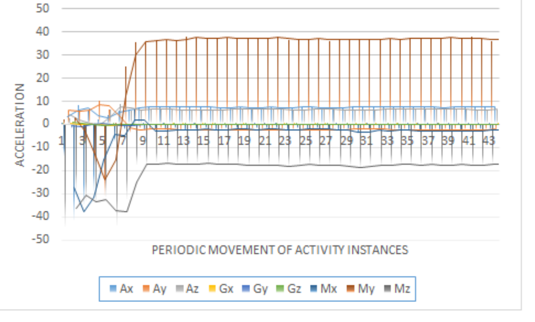
4.3 | Activity Representation Analysis

We chose 15 activities to recognize: *standing*, *sitting*, *sitting cross leg*, *sitting left leg over right*, *sitting right leg over left*, *walking normal*, *walking fast*, *jogging*, *fast running*, *laying straight*, *Laying Over Right Side (Lateral Right Position)*, *Laying Over Left Side (Lateral left Position*, *cycling*, *Upstairs and Downstairs*. We select these activities because these activities are performed regularly by users. By analyzing data, we saw that some activities represent a similar pattern and some show distinct behavior and pattern.

Figure 3 and 4 plots the accelerometer, gyroscope and magnetometer data of the fifteen activities. It can be clearly seen that sitting activity in Subfigures (3a, 3b, 3c,3d), standing activity in 3e and laying activity in Subfigures (3f, 3g, 3h) do not depict periodic pattern but do have distinctive patterns, based on the relative magnitudes of the x, y, and z-axis values for each of the sensors, while the all other activities, which involve repetitive motions, do depict periodic pattern. For most activities, the values of the y-axis have the largest accelerations. This is due to Earth's gravitational pull, which causes the accelerometer to measure a value of 9.8 $m/s2$ in the direction of the Earth's center.



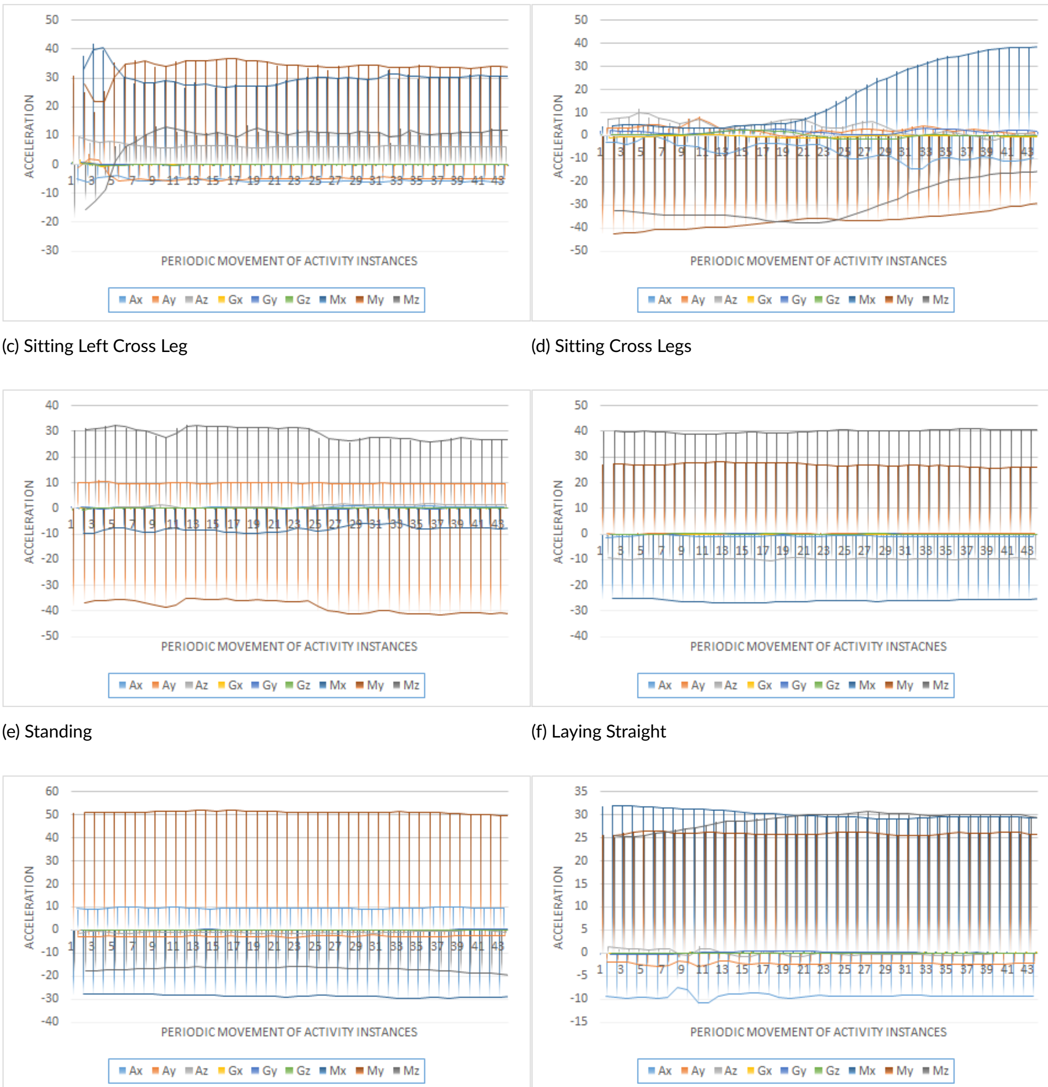
(a) Sitting Straight



(b) Sitting Right Cross Leg

The periodic patterns for walking are shown in Subfigures (4a, 4b), jogging in Subfigures (4c, 4d), ascending stairs descending stairs in Subfigure (4e, 4f), and cycling are shown in Subfigure 4g can be described in terms of the periodic peaks between each repetition of activity instance for each sensor and by the relative magnitudes of the acceleration values. The graph plot for walking shows a continuous series peaks along the y-axis and z-axis of the accelerometer. The distance between the peaks is also continuous. It can be observed that the repetitive activities represent a continuous peak to peak behavior.

Cycling, upstairs and downstairs in Subfigures (4e, 4f, 4g) shares similar repetitive behavior that is why the machine learning model confuses these activities with each other and same is the reason with walking and running, model confuses these with each other as well.



(c) Sitting Left Cross Leg

(d) Sitting Cross Legs

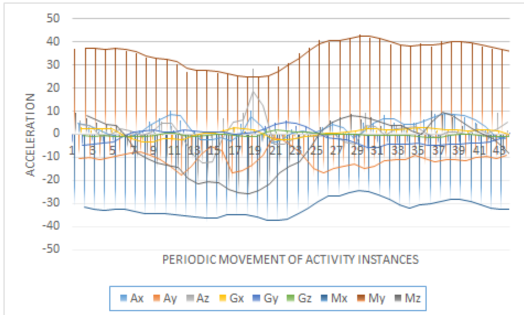
(e) Standing

(f) Laying Straight

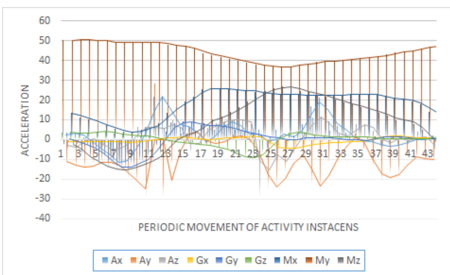
(g) Laying Over Left Side

(h) Laying Over Right Side

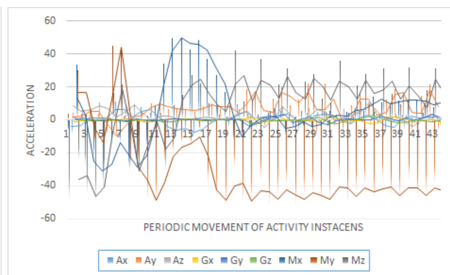
FIGURE 3 Acceleration Plots for the Stable Physical Activities using Three Smartphone Sensors: Accelerometer, Gyroscope, and Magnetometer



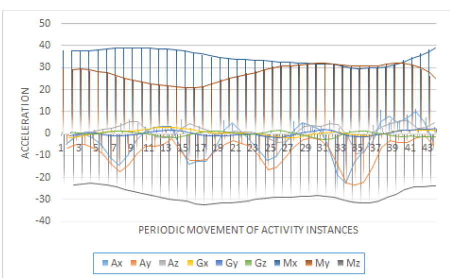
(a) Walking Normal



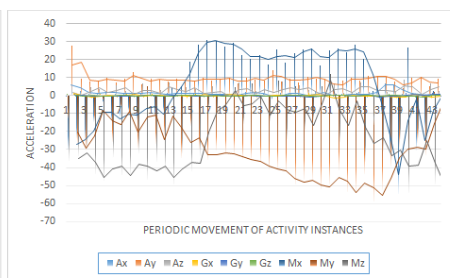
(b) Walking Fast



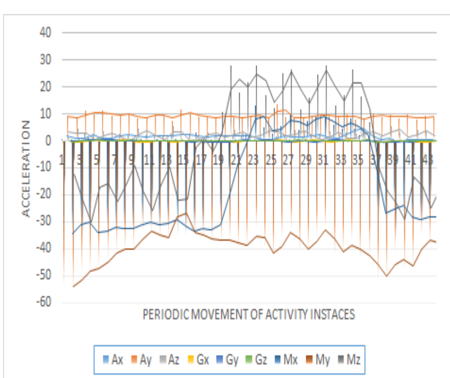
(c) Jogging



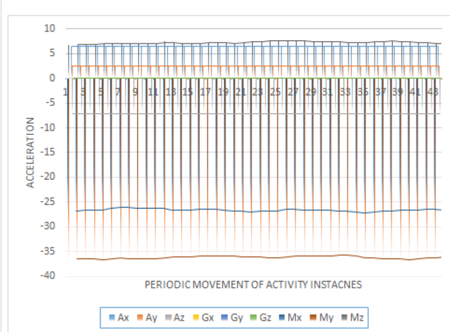
(d) Running Fast



(e) Upstairs



(f) Downstairs



(g) Cycling

FIGURE 4 Acceleration Plots for the Periodic Physical Activities using Three Smartphone Sensors: Accelerometer, Gyroscope, and Magnetometer

4.4 | Results

The detailed results of *PARCIV* are shown in Table 4. The Table shows the precision, recall, f-score and accuracy metric of each activity. *PARCIV* achieved the best accuracy for simple activities as well as activities having complex inter-class variations. *PARCIV* achieved 100% precision, recall, f-score and accuracy for activities 'Sitting Right Cross Leg', 'Cross Leg', 'Standing', 'Sitting Left Cross Leg', 'Straight Laying', 'Sitting Straight', 'Laying Over Left Side', 'Laying Over Right Side' and 'Cycling'. *PARCIV* also achieved 98% precision, recall, f-score and accuracy in case of activities having complex inter-class variations (i.e., Upstairs, Downstairs, Fast Running, Fast Walking, Jogging and Walking Normal). The most difficult activities to recognize have fewer inter-class variations and have fewer instances than others due to difficulties in performing these activities. The data balancing phase gives an advantage to this problem for increasing the variance. We achieved 99% precision, recall, f-score and accuracy on average for all 15 types of physical activities that show the effectiveness of *PARCIV*. The confusion matrix in Figure 5 ensure the reliability of *PARCIV*. This matrix illustrates how many examples of each activity often confused with the other activities. It shows that the maximum confusion is only 3% of 'Walking Normal' with the 'Fast Walking' activity. It also shows that all other activities are recognized efficiently with minimal confusion.

TABLE 4 Results with Evaluation Measures of each Activity using *PARCIV*. The Precision, Recall and Accuracy are in Percentage and the F-score is in Range [0,1]

Activities	Precision%	Recall%	f-Value	Accuracy%
Upstairs	98.5	99.2	0.99	97.7
Sitting Right Cross Leg	100.0	99.9	0.99	99.9
Fast Running	98.6	98.03	0.98	96.7
Jogging	98.25	96.9	0.98	95.3
Downstairs	98.5	99.5	0.99	98.05
Cross Leg	100.0	99.97	0.99	99.98
Standing	100.0	99.7	0.99	99.7
Fast Walking	96.03	98.03	0.97	94.2
Sitting Left Cross Leg	100.0	99.9	0.99	99.9
Walking Normal	95.8	96.3	0.96	92.4
Straight Laying	100.0	99.98	0.99	99.98
Sitting Straight	100.0	100.0	0.1	100.0
Laying over Left Side	100.0	100.0	0.1	100.0
Laying over Right Side	100.0	100.0	0.1	100.0
Cycling	100.0	100.0	0.1	100.0
Avg.	99.04	99.16	0.99	98.2

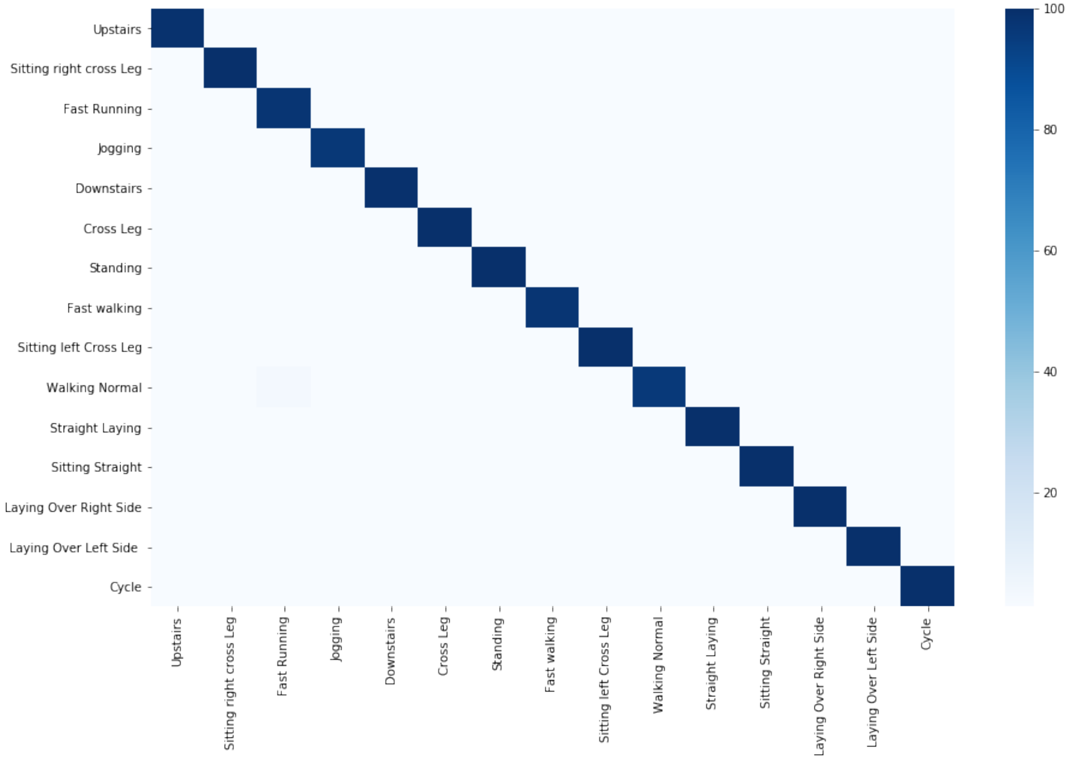


FIGURE 5 Confusion Matrix of *PARCIV*

4.5 | Comparative Analysis

We present overall performance comparison in Table 5 by using evaluation measures: precision, recall, f-score and accuracy. The confusion matrices presents more detailed results for activities having complex inter-class variations. It shows the distribution of true positive, true negative, false negative and false positive instances concerning each activity. The previous studies on smartphone-based physical activity recognition reports the accuracy between 70.0% and 97.0%. Accuracy is not a good measure when it comes to the different sample sizes of each activity class. In [2], authors claimed that their MCODE algorithm is more robust than K-means but their results show 10% lower accuracy than our approach based on K-means. In [37], the authors show only the accuracy measure which is equivalent to our approach. They did not show other evaluation measures and confusion matrix to validate variations that exist between activities. The study [23], used a high computational cost algorithm CNN on dynamic features that even provides less accuracy than our approach. The study [24] also used a high computational cost algorithm DBN with 60 and 20 neurons in hidden layers and gained 3% less accuracy than our approach. The study [27], applied five classifiers: MLP, SVM, RF and Logit Boost (LG). They got the highest 90% accuracy with an ensemble method of MLP, LG, and SVM. In [21], authors used a self-collected dataset of five common activities and only consider accuracy which is 10% lower than our approach. Their confusion matrix shows that most activities were wrongly recognized as walking.

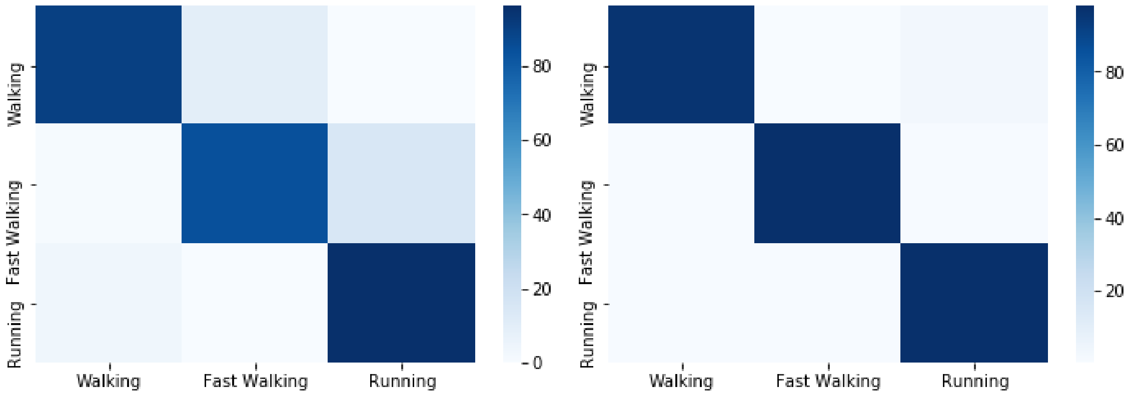
The confusion matrix in Figure 6 presents the comparison of *PARCIV* with state-of-the-art study [2]. It demonstrates that *PARCIV* provides more accurate results on three common activities having complex inter-class variations.

It shows that *PARCIV* achieved 6%, 14%, and 2% higher score than [2] for walking, fast walking, and running activities respectively.

The bar graph in figure 7 presents the comparison results of proposed approach *PARCIV* with the study [20] and [16] using f-score on [16] dataset. Authors in [20] used ensemble method based on SVM. Its analysed that our proposed approach *PARCIV* outperforms of 16%, 17%, 20% and 12% than [20] on walking, jogging, upstairs and downstairs activities respectively. In comparison of [16], *PARCIV* gives 10%, 3%, 32% and 36% higher f-score on walking, jogging, upstairs and downstairs activities respectively.

TABLE 5 Comparison of *PARCIV* with State-of-the-art Approaches

Approach	Dataset	Activities	Splitting	Precision	Recall	F-Score	Accuracy
PARCIV	**Self Collected**	**Table 3**	**Ten-Fold**	**99.04**	**99.16**	**0.99**	**98.2**
PARCIV	**[16]**	**Walking, Jogging, Sitting, Upstairs, Downstairs, Standing**	**Ten-Fold**	**94.04**	**93.86**	**0.94**	**95.2**
[2]	[16, 38]	Walking, Fast Walking, Running	NA	83.0	89.0	0.85	88.0
[37]	[39, 37]	Sitting, Standing, Laying, Walking, Upstairs, Downstairs	Train=70% Test=30%	NA	NA	NA	97.3, 98.8
[23]	[39]	Sitting, Standing, Laying, Walking, Upstairs, Downstairs	Train=70% Test=30%	NA	NA	NA	90.5
[24]	[39]	Standing, Sitting, Lying, Walking, Upstairs, Downstairs, Stand-Sit, Sit-Stand, Sit-Lie, Lie-Sit, Stand-Lie, Lie-Stand	Train=70% Test=30%	NA	NA	NA	95.8
[18]	[18, 39]	Standing, Walking, Running, Jumping,Cycling, Driving, Upstairs, Downstairs.	NA	96.9	96.9	96.9	99.2
[21]	[21]	Static, Walking, Running, Upstairs, Downstairs	Ten Fold	NA	NA	NA	89.6
[8]	[8]	Walk, Sit, Stand, Jogging, Biking, Upstairs , Downstairs	Ten Fold	NA	NA	NA	90.0
[27]	[27]	Slow Walk, Fast Walk, Running, Stairs-Up, Stairs-Down, Dancing	Ten Fold	NA	NA	NA	90.0
[20]	[16]	Walking, Jogging, Sitting, Upstairs, Downstairs	Train = 40%, Validate = 30% Test = 30%	NA	NA	82.0	NA
[16]	[16]	Walking, Jogging, Sitting, Upstairs, Downstairs, Standing	Ten Fold	NA	NA	91.7	NA



(a) Confusion matrix of the existing study [2]

(b) Confusion matrix of *PARCIV*

FIGURE 6 Confusion Matrix Comparison with state-of-the-art

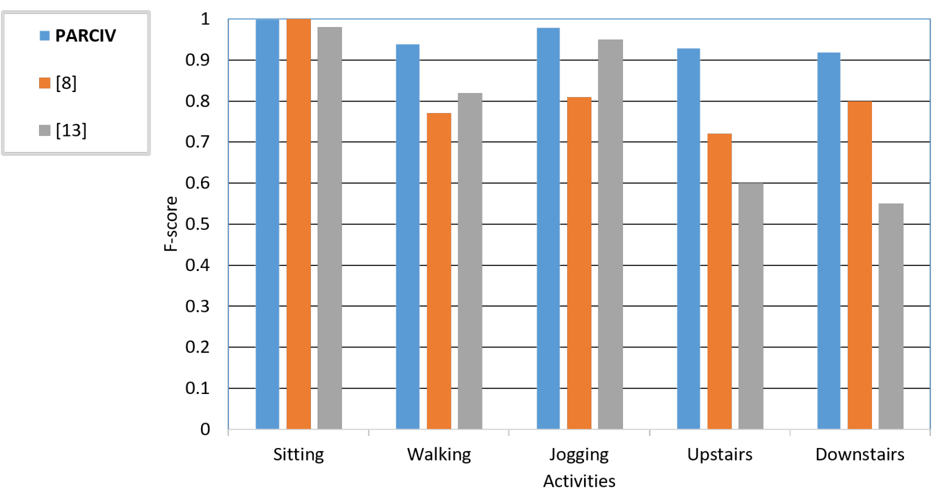


FIGURE 7 Bar graph Illustrating Comparison Results of *PARCIV* with the Existing Study [20] and [16] using f-score on [16] Dataset

4.6 | Discussion

Table 4 shows the best performance of 98.2% of our model on a self-collected dataset having activities having complex inter-class variations (i.e., Upstairs, Downstairs, Walking Normal, Walking Fast and Laying positions). We also evaluate our approach on [16] dataset and shows the comparison with the studies that used the same dataset. As in figure 7, it shows that our proposed approach *PARCIV* outperforms than [16] and [20]. We generally achieve 96%-99% accuracies for all activities including complex inter-class activities. The activities standing and sitting appears to be easier to recognize than other activities because of the still acceleration readings. It is analyzed that upstairs, downstairs, jogging, running and laying positions were more difficult to recognize because these similar activities have less inter-class variations since confused with each other. The Table 5 shows a quality comparison of *PARCIV* with state-of-the-art studies [2, 37, 23, 23, 24, 27, 21] on [16] dataset. Although existing work on smartphone-based physical activity recognition shows an accuracy between 70.0% and 97.0%. These variations can be due to: the dataset, the machine learning algorithm, hyper-parameter tuning, only used a specific set of activities and when the testing set is too small (i.e., 20%).

5 | CONCLUSION AND FUTURE WORK

In this paper, a two-layered approach *PARCIV* is proposed that recognizes simple as well as activities having complex inter-class variations on a fine-grained level. *PARCIV* first group similar activities based on semantic data using the k-Means clustering algorithm and then recognize different similar activities using the kNN classification algorithm on a fine-grained level. We collected labeled data from smartphone sensors: accelerometer, gyroscope, and magnetometer for the evaluation of *PARCIV*. Ten participants were asked to performed activities while keeping the smartphone in the pocket. *PARCIV* achieved an accuracy of 96%-99% for the recognition of fifteen activities on the self-collected dataset and 95.2% for the recognition of six activities on [16] dataset. Our experimental results show that the proposed method is practical and capable of increasing the recognition rate of normal physical activities as well as complex activities having complex inter-class variations. Moreover, it is shown that our proposed approach provides almost a 15% higher recognition rate than the state-of-art methods, primarily for activities having complex inter-class variations (e.g., walking normal, fast walking, upstairs, downstairs, laying positions).

In the future, we intend to recognize more complex physical activities. we plan to enhance the recognition process in the following way: 1) using deep learning methods to extract patterns for overlapping activities 2) gathering data from many users which belong to different age groups including old ages 3) gathering data from cognitively impaired individuals to correlate their health with physical activity patterns.

conflict of interest

The authors declare no potential conflict of interest.

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